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DESIGN OF A BIOGAS SYSTEM FOR ELECTRICITY GENERATION IN HOTELS SND RESIDENTIAL FACILITIES: A CASE STUDY IN CAMEROON

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ABSTRACT
The growing dependence of hotels and residential facilities in Cameroon on diesel-powered backup electricity, coupled with increasing volumes of biodegradable waste, creates an opportunity for decentralized renewable-energy generation through anaerobic digestion. This study presents the design and performance assessment of a fixed-dome biogas system for electricity generation, using a case study facility in Buea, Southwest Region, Cameroon. The BRC fixed-dome design methodology was applied to the co-digestion of human excrement and food waste using primary operational data obtained from the facility. The resulting system has a total digester volume of 3.44 m³, a diameter of 1.97 m, a 25-day hydraulic retention time, and an optimal total-solids concentration of 8%. The designed system is projected to produce 3.52 m³ of biogas daily, equivalent to approximately 5.98 kWh of electricity per day. At a diesel price of 800 FCFA/L, this energy recovery corresponds to monthly savings of approximately 41,040 FCFA, representing a 9.1% reduction in the facility's baseline monthly diesel expenditure of 450,000 FCFA. Scalability analysis indicates that the design methodology can be adapted to hotels and residential facilities of different capacities. Although technically viable, standalone implementation remains economically constrained, highlighting the potential importance of government subsidies, centralized multi-facility biogas systems, and supportive renewable-energy policies for wider adoption in Cameroon.

Keywords:
Biogas; Anaerobic Digestion; Fixed-Dome Digester; Electricity Generation; Organic Waste; Cameroon

1. INTRODUCTION

1.1 Energy Reliability and Organic-Waste Challenges in Hotels and Residential Facilities

Reliable electricity remains a persistent operational challenge for hotels and residential facilities in Cameroon, where supply interruptions and load shedding affect commercial and household activities [1]. Growing electricity demand, constrained generation capacity, and variability in hydropower availability further increase the vulnerability of grid-dependent facilities [2]. Hotels consequently rely on diesel generators to maintain refrigeration, lighting, water pumping, catering, security, and other essential services during outages [3]. This dependence increases operating expenditure and exposure to fuel-price fluctuations while reinforcing fossil-fuel consumption. Simultaneously, hospitality and residential facilities continuously generate food residues, human excrement, and other biodegradable wastes that are frequently disposed of without energy recovery [4]. The coexistence of concentrated organic waste and continuous electricity demand creates an opportunity for decentralized resource recovery. Anaerobic digestion can integrate waste treatment, renewable gas production, and decentralized electricity generation, converting locally available organic materials into biogas while producing digestate that can potentially be utilized as an organic soil amendment [5]. The interaction between facility energy demand, organic-waste generation, resource recovery, and diesel-dependent backup electricity is conceptualized in Figure 1.

1.2 Biogas Technology and Fixed-Dome Digestion

Anaerobic digestion converts biodegradable organic matter into biogas through hydrolysis, acidogenesis, acetogenesis, and methanogenesis under oxygen-free conditions [5]. The resulting gas typically contains approximately 50–70% methane and 30–45% carbon dioxide, together with smaller quantities of hydrogen sulfide and water vapour [4]. Its methane content provides the chemical energy required for thermal applications or electricity generation through an appropriate gas engine-generator system. Fixed-dome digesters are particularly relevant to Sub-Saharan African applications because their underground masonry construction provides durability, limited moving components, relatively low maintenance requirements, and integrated gas storage [6]. Co-digestion of food waste and human excrement can improve substrate availability and nutrient balance compared with dependence on a single waste stream [7]. However, actual performance remains sensitive to

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feedstock characteristics, dilution water, temperature, organic loading, retention time, and construction quality [8]. The daily substrate balance is expressed as

$$M_s = M_f + M_h + M_w \qquad (1)$$

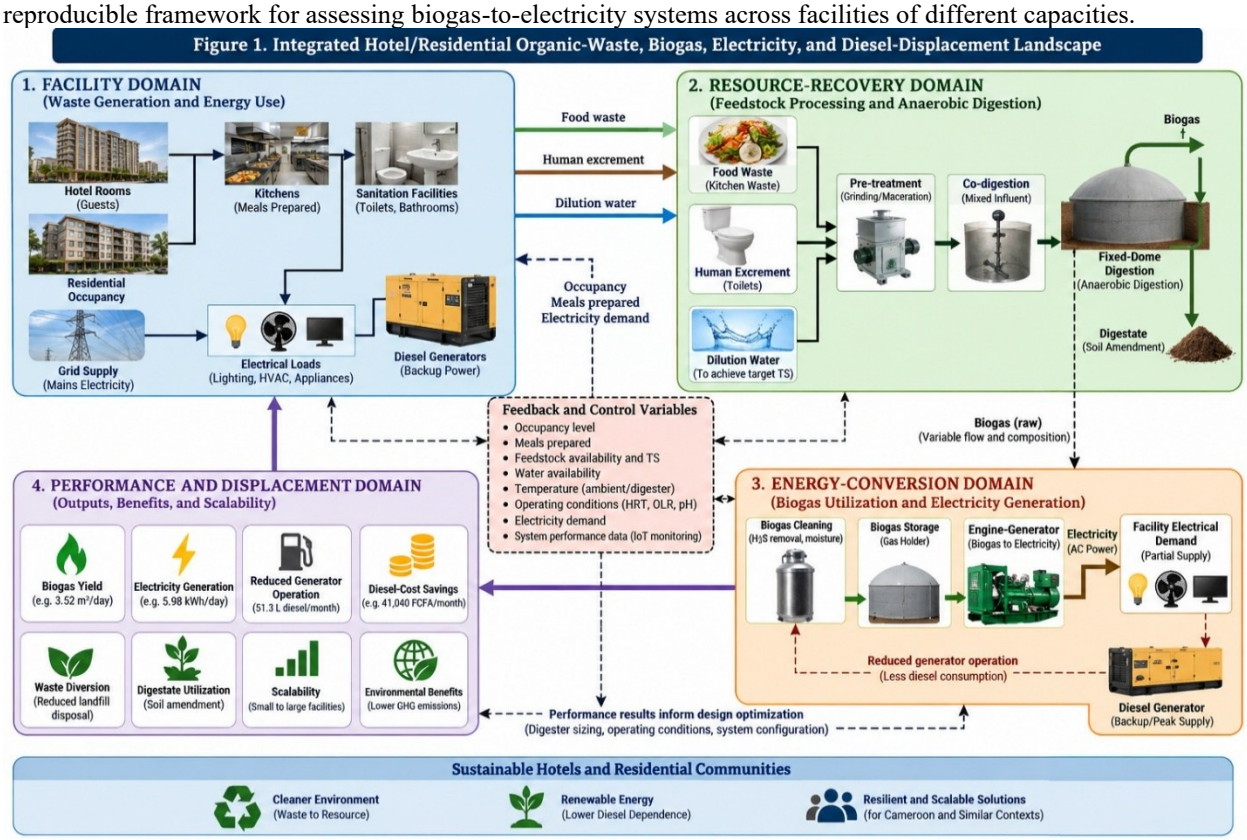
where M_s is the total daily slurry input, M_f is the food-waste mass, M_h is the human-excrement mass, and M_w is the dilution-water input.

1.3 Research Gap, Aim, and Contributions

Although biogas technologies have been extensively investigated for organic-waste treatment and renewable-energy recovery, many design approaches evaluate gas production independently of facility-specific electricity requirements, diesel displacement, operational variability, predictive performance, and system scalability [6]. This separation limits understanding of whether technically feasible digesters can deliver meaningful energy and economic benefits under actual hotel and residential operating conditions [8]. The present study therefore asks: *How can a fixed-dome biogas system be designed, optimized, and evaluated for reliable electricity recovery from organic waste generated by hotels and residential facilities in Cameroon?* Using primary operational data from a hospitality facility in Buea, Southwest Region, the study integrates engineering design with data-driven performance assessment [9].

Specifically, it characterizes facility waste generation and electricity demand; designs and sizes the fixed-dome digester; engineers operational predictors of biogas and electricity output; develops and validates predictive performance models; benchmarks predicted and calculated performance against reference operating conditions; and evaluates diesel displacement, economic feasibility, scalability, and practical deployment. Figure 1 presents the overarching conceptual landscape of this integration. Rather than representing biogas production as an isolated linear conversion process, it links four interacting domains: facility operation, resource recovery, energy conversion, and performance and displacement. Occupancy and meals prepared determine feedstock availability, while electricity demand influences the value of recovered energy. Feedstock characteristics, dilution water, temperature, and operating conditions subsequently influence digester sizing and achievable biogas production. The resulting electricity reduces diesel-generator operation, while performance outcomes provide feedback for system sizing, operating optimization, and scalability assessment. This integrated approach establishes a reproducible framework for assessing biogas-to-electricity systems across facilities of different capacities.

Figure 1. Integrated Hotel/Residential Organic-Waste, Biogas, Electricity, and Diesel-Displacement Landscape



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2. CASE-STUDY DATA ACQUISITION AND BIOGAS SYSTEM DESIGN

2.1 Case-Study Facility and Primary Data Acquisition

The design was developed from a hospitality facility located in Buea, Southwest Region, Cameroon, hereafter referred to as Hotel X to preserve confidentiality. The facility accommodates approximately 50 persons per day, prepares about 25 meals daily, and uses diesel generation to supplement unreliable grid electricity, with an average reported fuel expenditure of 450,000 FCFA per month [8]. Primary operational information was obtained through direct engagement with facility management and structured observation of waste, energy, and utility activities. Data acquisition covered occupancy, food-waste generation, availability of human excrement, water supply, electricity consumption, generator operating duration, diesel consumption and expenditure, ambient temperature, and existing waste-disposal practices [9]. Waste and generator variables were treated at daily resolution, while electricity and temperature could be represented at hourly or daily intervals depending on record availability [10]. Repeated measurements were checked for unit consistency, impossible values, missing observations, and abrupt recording errors before analysis [12]. Where direct measurements were unavailable, operational records or occupancy-based estimates were distinguished from physically measured observations to prevent uncertainty from being interpreted as measured performance [14].

Table 1. Case-Study Data Sources, Measured Variables, Units, and Analytical Functions

Data Source	Variable	Unit	Frequency	Acquisition Method	Analytical Function
Facility occupancy	Guests/residents present	persons/day	Daily	Management records	Human-waste and demand estimation
Kitchen operation	Meals prepared	meals/day	Daily	Catering records	Food-waste normalization
Food waste	Daily biodegradable mass	kg/day	Daily	Weighing/recording	Primary feedstock estimation
Sanitary waste	Human-excrement quantity	kg/day	Daily	Occupancy-based estimate/measurement	Co-substrate input
Water supply	Dilution water availability	L/day	Daily	Facility records/measurement	Slurry preparation
Electricity	Facility demand	kWh/day	Hourly/Daily	Meter/operational records	Electrical-load benchmark
Generator	Operating duration	h/day	Daily	Generator log	Backup-energy requirement
Generator	Diesel consumption	L/day	Daily	Fuel/operational records	Diesel displacement
Finance	Diesel expenditure	FCFA/month	Monthly	Management records	Economic benchmark
Environment	Ambient temperature	°C	Hourly/Daily	Sensor/weather record	Digestion-condition assessment
Waste management	Disposal pathway	categorical	Observation period	Site observation/interview	Baseline environmental practice

2.2 Feedstock Characterization and Slurry Preparation

The proposed digester utilized co-digested food waste and human excrement, reflecting waste streams generated continuously by hotel kitchens and sanitation facilities [10]. Feedstock characterization considered total solids (TS), volatile solids (VS), moisture content, substrate mixing ratio, dilution requirement, co-digestion proportion, and organic loading [13]. Total solids were calculated from wet and dry sample masses as

$$TS(\%) = \frac{M_{\text{dry}}}{M_{\text{wet}}} \times 100 \qquad (2)$$

where $M_{\text{dry}}$is the mass remaining after moisture removal and $M_{\text{wet}}$is the original wet feedstock mass. VS represents the biodegradable organic fraction of the solids and therefore provides a stronger indication of potential methane-producing material than wet mass alone [7]. Moisture content controls pumpability and substrate mobility, whereas dilution water determines the slurry concentration introduced into the digester [12]. An 8% TS

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concentration was adopted as the target operating condition to maintain sufficiently fluid slurry movement while avoiding excessive dilution. As illustrated in Figure 2, this feedstock condition is established at the inlet/mixing stage before the prepared slurry enters the principal digestion chamber. This consideration is important in Cameroon because water availability and inappropriate solids concentration can significantly modify actual fixed-dome digester performance [8].

2.3 Hydraulic Retention Time and Digester Sizing

Hydraulic retention time establishes the average period for which introduced slurry remains within the active digestion chamber and therefore directly links daily feeding rate with required digester capacity [11]. For the case-study system, a 25-day HRT was adopted within the BRC fixed-dome design methodology. The active digestion-volume relationship was expressed as

$$V_D = Q_s \times HRT \qquad (3)$$

where V_D is the effective digestion volume in m³, Q_s is the daily prepared-slurry input in m³/day, and HRT is the hydraulic retention period in days. Thus, increasing daily slurry input or retention time proportionally increases the biological volume required to prevent premature substrate displacement [12].

Application of the BRC dimensional procedure, including allowances for digestion space, gas accumulation, and hydraulic displacement, produced a total system volume of 3.44 m³, a working volume of 2.75 m³, and a principal digester diameter of approximately 1.97 m. Figure 2 presents the resulting BRC fixed-dome geometry and relates the principal design parameters directly to their corresponding physical regions. The daily slurry input and 8% TS condition are associated with the inlet and mixing chamber, while the 25-day HRT and working volume govern the capacity of the digestion chamber. The 3.44 m³ total volume and 1.97 m diameter define the overall digester geometry, including the digestion space and upper fixed gas dome.

As shown in Figure 2, prepared slurry enters through the inlet/mixing chamber and passes into the underground anaerobic digestion chamber, while generated biogas accumulates beneath the fixed dome and is withdrawn through the gas outlet. Changes in gas pressure hydraulically displace slurry toward the displacement chamber and digestate outlet. During gas accumulation, the slurry level shifts toward the outlet chamber; when gas is withdrawn, pressure decreases and the slurry level partially returns [11]. This hydraulic arrangement eliminates the need for a mechanically moving gas holder and contributes to the structural simplicity and durability associated with fixed-dome systems [8]. Figure 2 therefore demonstrates that feed rate, solids concentration, HRT, working volume, total volume, and diameter operate as interdependent design parameters rather than isolated sizing variables. Correct system performance consequently depends on maintaining the intended feedstock preparation and operating conditions [14].

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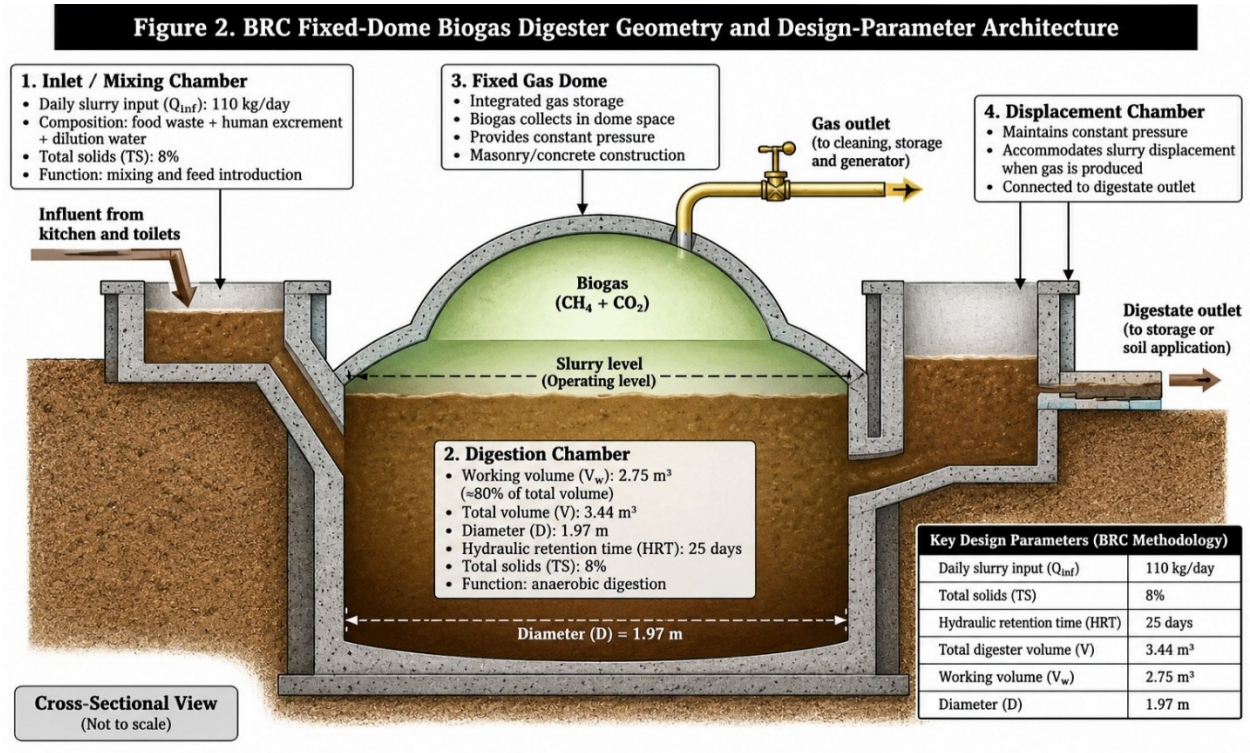

Figure 2. BRC Fixed-Dome Biogas Digester Geometry and Design-Parameter Architecture

2.4 Integrated Biogas-to-Electricity System Architecture

The complete system was configured as an integrated material-and-energy conversion chain extending beyond the digester itself [9]. As illustrated in Figure 3, food residues and sanitary-derived substrates are collected separately to reduce contamination by non-biodegradable materials before entering the conversion system. Food waste is sorted and size-reduced before being combined with human excrement and the calculated quantity of dilution water to achieve the target slurry concentration [13]. The homogenized feed enters the fixed-dome digester, where anaerobic microorganisms convert biodegradable organic matter into methane-rich biogas and stabilized digestate [7]. Produced gas accumulates within the dome before passing through moisture removal and hydrogen-sulfide treatment to protect downstream piping and generation equipment [11].

Figure 3 shows the subsequent energy-conversion pathway, in which conditioned biogas is supplied to a suitably sized gas engine-generator and converted into electricity for the facility's electrical loads. The recovered electricity consequently reduces the operating requirement of the diesel generator rather than assuming complete replacement of the existing backup system [8]. Digestate leaving the displacement chamber is collected separately for controlled handling and potential agricultural utilization.

Importantly, Figure 3 also connects the physical conversion system with the subsequent analytical framework. Operational measurements obtained across the facility, feedstock, digester, environmental, gas-production, electricity-generation, and diesel-consumption stages provide the variables required for feature engineering and performance prediction in Section 3. These measurements enable the physical behaviour of the biogas system to be represented quantitatively rather than treating the digester as an isolated conversion unit. The architecture therefore integrates waste management, feedstock preparation, anaerobic conversion, gas conditioning, electricity recovery, diesel displacement, digestate recovery, and operational data acquisition within a single decentralized facility-level framework [14].

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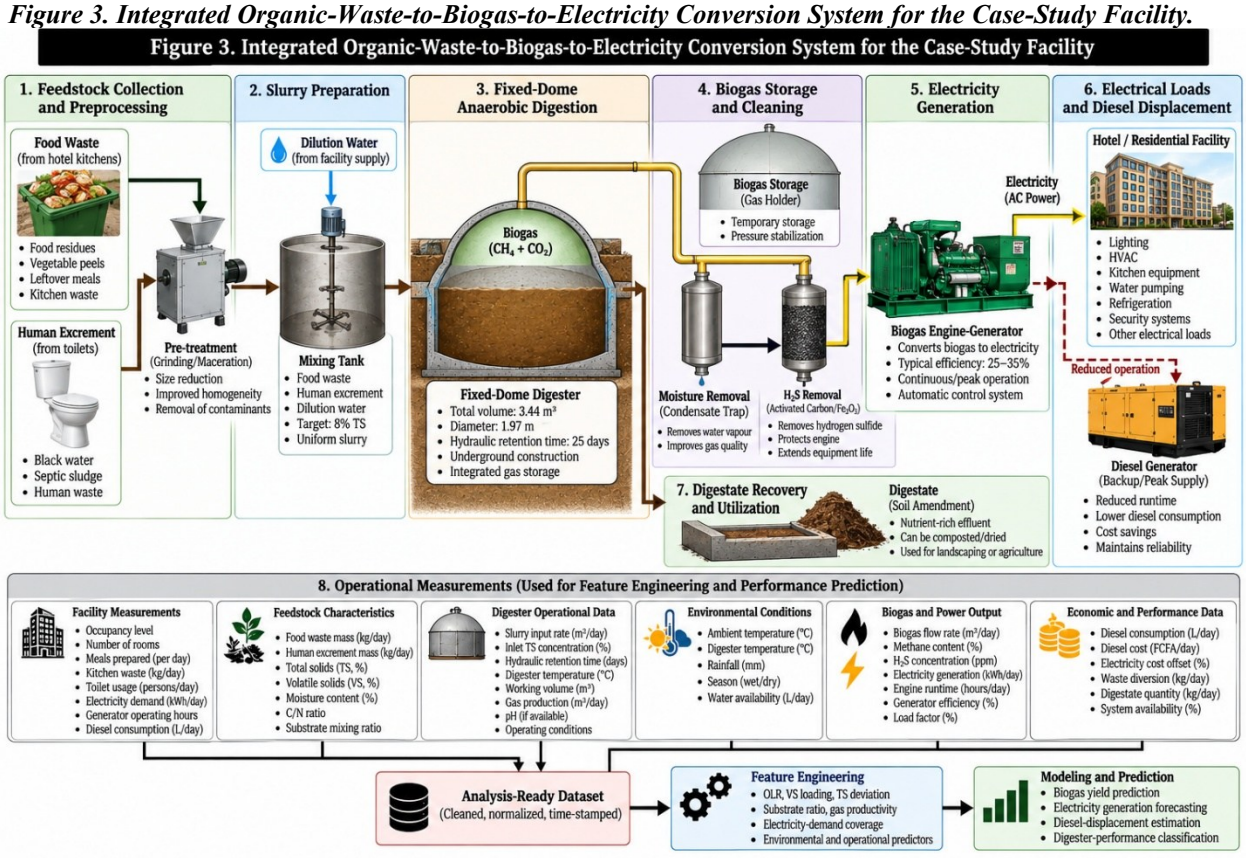
Figure 3. Integrated Organic-Waste-to-Biogas-to-Electricity Conversion System for the Case-Study Facility.



3. FEATURE ENGINEERING AND BIOGAS-ENERGY PERFORMANCE REPRESENTATION

The engineering calculations developed from the case-study feedstock and digester design were converted into structured analytical variables for subsequent predictive modelling. Rather than using raw measurements independently, the feature-engineering stage combined feedstock composition, digester operating conditions, environmental factors, gas-production characteristics, and electricity-demand indicators into a unified dataset capable of representing the biological and energy-conversion behaviour of the proposed system [12].

3.1 Raw Operational and Environmental Features

The initial predictor set comprised variables obtained directly from facility measurements, design calculations, and operating records. These included daily food-waste mass, human-excrement mass, total solids (TS), volatile solids (VS), water-to-feedstock ratio, hydraulic retention time (HRT), ambient temperature, organic loading conditions, facility occupancy, daily slurry volume, historical biogas production, and electricity demand [13]. The variables were separated into static design features and dynamic operational features. Static variables included digester volume, diameter, nominal HRT, target TS concentration, and fixed geometric dimensions established during system sizing [14]. Dynamic variables included daily waste availability, occupancy, temperature, slurry input, electricity demand, and observed gas production, all of which could vary across operating periods [15]. This distinction was important because fixed design parameters determine system capacity, whereas dynamic variables describe actual conditions affecting biological conversion and usable energy output [16]. Together, these features provided the foundation for characterizing temporal variation in digester performance.

3.2 Engineered Digestion and Loading Features

Additional predictors were constructed from the raw variables to describe digestion intensity and operating deviation more effectively [17]. These included daily VS loading, specific substrate loading, food-waste-to-human-waste ratio, water-to-feedstock ratio, temperature deviation from the selected mesophilic condition, TS deviation from the 8% target, occupancy-normalized waste generation, specific gas productivity, and rolling waste availability [18]. Organic loading rate was defined as

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$$OLR = \frac{M_{VS}}{V_D} \qquad (4)$$

where $OLR$is the organic loading rate in kg VS m $^{-3}$ day $^{-1}$, $M_{VS}$is the daily mass of volatile solids introduced into the digester in kg VS/day, and $V_D$is the active digestion volume in m³. The expression is obtained by dividing the biodegradable organic mass entering the reactor each day by the effective volume available for anaerobic conversion [19]. Normalizing feed input by digester volume permits meaningful comparison between operating days and different facility scales. Excessive OLR may cause volatile-fatty-acid accumulation and process instability, whereas very low loading can underutilize available digester capacity [20].

3.3 Biogas and Electrical-Energy Features

Biogas-generation features were derived from the biodegradable solids contained in each substrate. Daily biogas volume was represented generally as

$$V_B = M_{VS} Y_B \qquad (5)$$

where $V_B$is daily biogas production in m³/day, $M_{VS}$is the available volatile-solids mass, and $Y_B$is the substrate-specific biogas yield in m³/kg VS [15]. For the case-study design, human excrement and food waste were evaluated separately before their predicted gas contributions were combined [16]. Food-waste VS was obtained from its TS fraction and assumed volatile-solids proportion, while human-waste yield was estimated from its corresponding solids loading [17]. Biogas production was then connected to methane fraction, gas calorific value, generator conversion efficiency, and the usable electricity produced from the gas stream [18]. Additional derived features included gas productivity per unit digester volume, electricity generated per cubic metre of biogas, diesel-equivalent energy displacement, and electricity-demand coverage [19]. These variables linked biological digestion performance directly with the facility's energy objective rather than treating gas production as an isolated outcome [20].

3.4 Feature Selection, Normalization, and Analytical Dataset

Before model development, the complete feature matrix was subjected to correlation analysis, multicollinearity screening, missing-value assessment, outlier detection, and standardization [12]. Highly redundant variables were removed where they provided limited additional information, while retained predictors were normalized to comparable scales before algorithms sensitive to variable magnitude were trained [14]. Feature-importance analysis was subsequently used to identify the strongest contributors to predicted biogas and electricity performance [16]. Missing values were either excluded or imputed according to data availability and variable type, while extreme observations were checked against operational records before removal [18].

As summarized in Figure 4, the analytical framework integrates five principal data domains: facility measurements, feedstock characteristics, digester-design and operating variables, environmental conditions, and energy-demand records. These raw variables are transformed into engineered predictors representing organic loading rate (OLR), VS loading, TS deviation, substrate ratio, gas productivity, and electricity-demand coverage. Figure 4 further illustrates the preprocessing stages through which the multi-source measurements are cleaned, normalized, temporally synchronized, and integrated before construction of the final analytical dataset.

Four analytical targets were constructed: daily biogas yield, electricity production, diesel displacement, and digester performance class [20]. The resulting analysis-ready dataset therefore provides a consistent representation of feedstock, digestion, environmental, and facility-energy behaviour. Figure 4 establishes the analytical connection between the physical measurements described in Section 2 and the predictive modelling architecture developed in Section 4, with the engineered features serving as model inputs for biogas prediction, electricity forecasting, diesel-displacement estimation, and digester-performance classification

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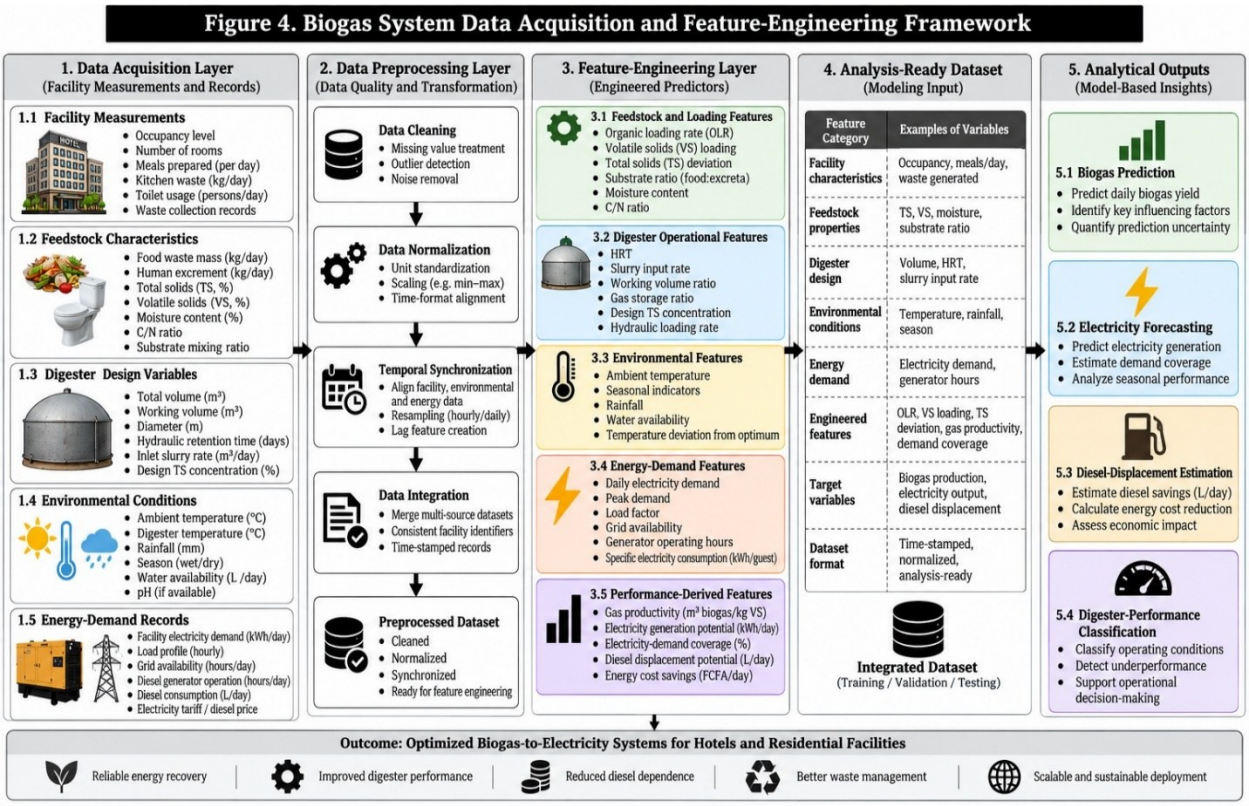

4. PREDICTIVE MODELLING, TRAINING, HYPERPARAMETER OPTIMIZATION, AND TESTING

4.1 Model Development and Benchmark Algorithms

The analysis-ready dataset developed from the engineered feedstock, digestion, environmental, and energy variables was used to construct predictive models for daily biogas production and associated electricity output [19]. Multiple linear regression (MLR) was adopted as an interpretable baseline because it provides direct relationships between individual predictors and system response [20]. More flexible nonlinear methods included random forest regression (RFR), gradient boosting regression (GBR), and support vector regression (SVR) to capture interactions between waste composition, organic loading, temperature, hydraulic conditions, and gas yield [21]. An artificial neural network (ANN) was additionally considered where the number and temporal coverage of observations were sufficient to support reliable parameter estimation without excessive overfitting [22]. The general predictive formulation was

$$\hat{V}_{B,t} = f(X_t; \theta) \qquad (6)$$

where $\hat{V}_{B,t}$is predicted biogas production at time t, $X_t$is the vector of engineered feedstock, environmental, loading, and operational features, and θdenotes model-specific parameters learned during training. Model comparison enabled assessment of whether nonlinear algorithms provided meaningful improvements over the transparent regression baseline [23].

4.2 Data Splitting and Training Phase

Model development followed a chronological 60:20:20 partition, with the earliest 60% of observations allocated to training, the subsequent 20% to validation, and the most recent 20% retained as a locked independent test set [20]. Chronological partitioning was preferred to unrestricted random sampling because facility occupancy, waste production, ambient conditions, and digester response can exhibit temporal dependence [22]. Random redistribution of adjacent observations between training and testing could therefore expose the model indirectly to future operating patterns, producing temporal data leakage and an overoptimistic estimate of generalization performance [23]. The training subset was used exclusively for learning regression coefficients, tree structures, support vectors, or neural-network weights. The validation subset supported feature refinement, hyperparameter selection, model comparison, and prediction-threshold decisions [24]. The locked test subset remained excluded from all optimization activities and was used only after final model selection to evaluate performance on unseen

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operating periods [25]. Preprocessing parameters, including means and standard deviations used for scaling, were estimated from training data and subsequently applied unchanged to validation and test observations to further prevent information leakage [26].

4.3 Hyperparameter Tuning and Model Optimization

Hyperparameter optimization was performed at the validation stage because the candidate algorithms contain controls that determine model complexity and generalization behaviour [21]. As illustrated in Figure 5, model development was separated from the independent testing stage, with the temporally ordered dataset partitioned into 60% training, 20% validation, and 20% locked-test subsets. The training and validation partitions supported model development and hyperparameter selection, whereas the locked-test partition remained isolated until final model evaluation.

For the random forest, tuned parameters included the number of trees, maximum tree depth, minimum observations permitted at terminal leaves, and fraction of predictors considered at each split [22]. For gradient boosting, the optimization space included learning rate, number of estimators, maximum tree depth, and subsampling ratio, thereby balancing sequential error correction against overfitting [23]. The principal SVR parameters were the regularization constant C, epsilon-insensitive margin ε, kernel specification, and kernel coefficient γ[24]. For the ANN, candidate architectures varied the number of hidden layers, neurons per layer, learning rate, batch size, and number of training epochs [25].

Figure 5 further shows that MLR, random forest, gradient boosting, SVR, and ANN are developed as parallel candidate models rather than as sequential modelling stages. For the nonlinear algorithms, candidate hyperparameter configurations are evaluated using validation performance and overfitting controls before the optimum configuration is selected. Grid search may be used for a restricted parameter space, whereas randomized search provides greater computational efficiency where numerous combinations are possible. Bayesian optimization may additionally be applied to concentrate evaluations on progressively promising parameter regions [26].

Importantly, the locked-test architecture shown in Figure 5 prevents test information from influencing hyperparameter selection. Only the finalized models with their selected parameters are exposed to the independent test subset. Their predictions are then evaluated in terms of biogas production, electricity generation, diesel displacement, residual errors, and the specified model-performance metrics. This separation preserves the test dataset as an unbiased estimate of model generalization and provides the basis for subsequent comparative benchmarking.

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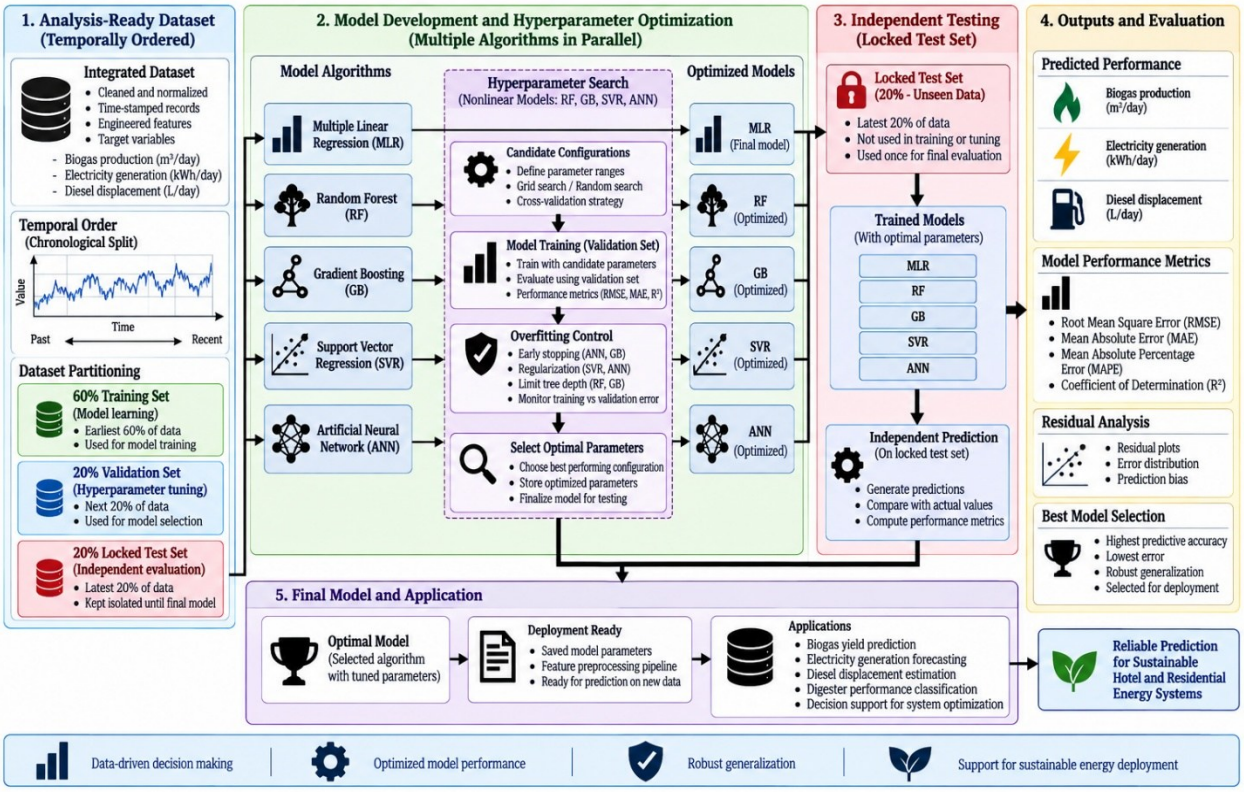
Figure 5. Model Training, Hyperparameter Optimization, Validation, and Independent Testing Architecture



4.4 Prediction Error and Performance Metrics

Predictive performance was evaluated using complementary metrics because no single statistic completely represents model accuracy [19]. Mean absolute error (MAE) quantified average absolute prediction error, while root mean square error (RMSE) imposed a larger penalty on substantial deviations [20]. The coefficient of determination, R^2, quantified the proportion of observed response variation represented by the model, whereas mean absolute percentage error (MAPE) expressed prediction error relative to observed magnitude [22]. Mean deviation was calculated as

$$MD = \frac{1}{n}\sum_{i=1}^{n}|\hat{y}_i - y_i| \qquad (7)$$

where $n$is the number of test observations, $\hat{y}_i$is the predicted response, and $y_i$is the corresponding observed or engineering-reference value. The equation is derived by first obtaining the prediction residual $e_i = \hat{y}_i - y_i$, taking its absolute magnitude to prevent positive and negative errors from cancelling, and then averaging the resulting deviations across all observations [24]. Consequently, a smaller MD indicates closer agreement between predicted and reference performance [25]. The standard deviation of residuals was additionally used to evaluate error dispersion, while mean signed error quantified systematic prediction bias. Models were therefore benchmarked jointly on accuracy, stability, bias, and their ability to generalize to the locked out-of-time dataset [26].

5. TECHNICAL PERFORMANCE, ELECTRICITY GENERATION, AND ECONOMIC ANALYSIS

5.1 Designed System Performance

Application of the BRC fixed-dome design methodology to the Hotel X feedstock produced a 3.44 m³ total digester volume, 1.97 m diameter, 2.75 m³ working volume, and 25-day hydraulic retention time, with influent adjusted to the selected 8% total-solids concentration [24]. The daily feedstock comprised 25 kg of human excrement and 19 kg of food waste, providing a combined 8.8 kg TS/day. Dilution required approximately 66 kg of water, producing 110 kg/day of prepared influent [25]. The human-excrement fraction generated an estimated 2.15 m³/day of biogas, while 3.04 kg VS/day from food waste contributed approximately 1.37 m³/day, giving a combined yield of 3.52 m³/day [26]. This corresponded to approximately 5.98 kWh/day of electricity. The results

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indicate that the available feedstock can sustain the calculated output provided the assumed daily occupancy, waste-generation rates, solids characteristics, dilution requirement, and operating conditions are maintained [27]. Variations in occupancy or recoverable food waste would consequently alter achievable gas production.

5.2 Biogas-to-Electricity Conversion Efficiency

The useful electricity obtainable from biogas depends not only on gas volume but also on methane concentration, its energy content, and generator efficiency [28]. The generalized energy-conversion relationship is

$$E_e = V_B \, x_{CH_4} \, LHV_{CH_4} \, \eta_e \qquad (8)$$

where E_e is electrical energy generated in kWh/day, V_B is daily biogas volume in m³/day, x_{CH_4} is the volumetric methane fraction, LHV_{CH_4} is the lower heating value of methane in kWh/m³, and η_e is generator electrical efficiency. Equation (8) is derived by first determining the methane volume, $V_B x_{CH_4}$, converting this volume into available chemical energy through LHV_{CH_4}, and multiplying by η_e to obtain useful electricity [29]. For the present design calculation, the adopted practical conversion factor of 1.7 kWh/m³ of biogas yielded $3.52 \times 1.7 \approx 5.98$kWh/day, equivalent to approximately 179.4 kWh/month [30].

5.3 Diesel Displacement and Economic Performance

The estimated 179.4 kWh/month of biogas-derived electricity was evaluated against Hotel X's existing diesel-generator operation. At an assumed generator output of 3.5 kWh per litre, the proposed system could displace approximately 51.3 litres of diesel per month [24]. Using the specified local diesel price of 800 FCFA/L, this corresponds to approximately 41,040 FCFA/month, or 492,480 FCFA/year, in avoided fuel expenditure. Relative to the facility's reported baseline expenditure of 450,000 FCFA/month, the direct diesel-cost offset is approximately 9.1% [26].

The positive fuel saving does not, however, establish standalone economic attractiveness. Capital expenditure for excavation, reinforced-concrete construction, piping, hydraulic chamber, gas treatment, storage, generator adaptation, and installation must be considered alongside routine operation and maintenance expenditure [28]. Simple payback should therefore be calculated from total investment divided by annual net savings after operating costs. Where reliable capital, maintenance, discount-rate, and equipment-life data are available, net present value (NPV) and levelized cost of electricity (LCOE) should provide stronger lifecycle indicators [31]. Waste-disposal savings and digestate value may improve the economics but should be quantified independently rather than assumed [32].

5.4 Scalability Across Facility Sizes

Scalability was assessed by applying the same feedstock-generation and conversion assumptions across progressively larger facility populations. As illustrated in Figure 6, facility size is considered together with recoverable organic-feedstock availability because population alone does not determine achievable biogas and electricity production. A small residential facility would generate comparatively limited feedstock and therefore require a smaller digester, but its capital cost per unit of electricity could remain relatively high [27]. A medium residential complex or small hotel would increase recoverable food and sanitary waste, producing correspondingly greater biogas and diesel displacement.

Hotel X is identified in Figure 6 as the 50-person reference design, with a 3.44 m³ digester volume, 3.52 m³/day biogas production, 5.98 kWh/day electricity generation, 51.3 L/month diesel displacement, and 41,040 FCFA/month fuel-cost saving. Under proportional scaling from this reference case, a 100-person facility could generate approximately 7.04 m³/day of biogas and 11.96 kWh/day of electricity, assuming equivalent per-capita waste availability and conversion conditions [29]. Larger hotels and multi-facility clusters could aggregate substantially greater feedstock quantities and potentially improve equipment utilization and economies of scale [31].

Figure 6 further represents scalability as a multidimensional relationship among facility size, recoverable feedstock, biogas production, electricity recovery, digester-volume requirement, diesel displacement, and fuel-cost savings. This representation emphasizes that increasing facility capacity affects several technical and economic parameters simultaneously rather than merely increasing biogas output. The uncertainty region associated with the scaled scenarios is particularly important because the values beyond the Hotel X reference case represent proportional design projections rather than measured operating performance.

Linear scaling should therefore be interpreted as a design scenario rather than guaranteed operating performance because waste composition, occupancy, temperature, collection efficiency, hydraulic loading, generator efficiency, and construction costs may not scale proportionally [32]. Consequently, larger applications require site-specific recalculation rather than simple multiplication of the Hotel X design. Figure 6 therefore provides a

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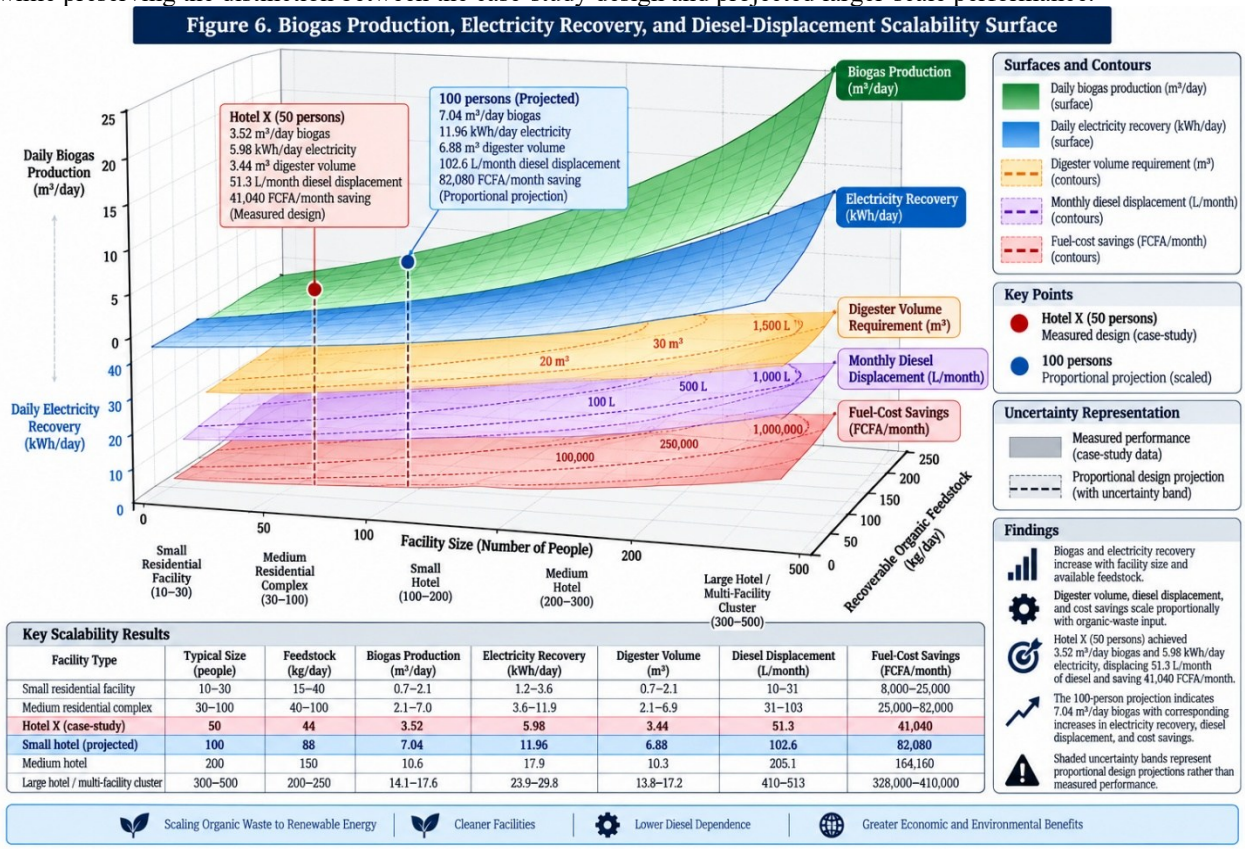
scalability framework for preliminary comparison across residential facilities, hotels, and multi-facility clusters while preserving the distinction between the case-study design and projected larger-scale performance.

Figure 6. Biogas Production, Electricity Recovery, and Diesel-Displacement Scalability Surface



Key Scalability Results

Facility Type	Typical Size (people)	Feedstock (kg/day)	Biogas Production (m³/day)	Electricity Recovery (kWh/day)	Digester Volume (m³)	Diesel Displacement (L/month)	Fuel-Cost Savings (FCFA/month)
Small residential facility	10–30	15–40	0.7–2.1	1.2–3.6	0.7–2.1	10–31	8,000–25,000
Medium residential complex	30–100	40–100	2.1–7.0	3.6–11.9	2.1–6.9	31–103	25,000–82,000
Hotel X (case-study)	**50**	**44**	**3.52**	**5.98**	**3.44**	**51.3**	**41,040**
Small hotel (projected)	**100**	**88**	**7.04**	**11.96**	**6.88**	**102.6**	**82,080**
Medium hotel	200	150	10.6	17.9	10.3	205.1	164,160
Large hotel / multi-facility cluster	300–500	200–250	14.1–17.6	23.9–29.8	13.8–17.2	410–513	328,000–410,000

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6. BENCHMARKING, STANDARDS COMPARISON, AND ROBUSTNESS ASSESSMENT

6.1 Benchmarking Against Alternative Design and Prediction Approaches

The deterministic BRC methodology produced a 3.44 m³ fixed-dome digester, with a working volume of 2.75 m³, diameter of 1.97 m, and hydraulic retention time of 25 days. From the calculated feedstock loading, the system generated a theoretical biogas output of 3.52 m³/day and electrical output of 5.98 kWh/day. These engineering results establish the deterministic baseline against which data-driven models can be evaluated [31]. Multiple linear regression provides the interpretable statistical benchmark, while random forest, gradient boosting, and support vector regression accommodate nonlinear relationships between feedstock, loading, temperature, and gas production [32]. ANN may additionally be evaluated where sufficient observations are available [33]. All models should use the same locked test observations and be compared through MAE, RMSE, MAPE, R^2, and mean deviation. Since experimental time-series model outputs were not generated in the present design calculations, predictive accuracy values are not artificially assigned.

Table 2. Predictive Model and Design-Method Benchmark

Model/Method	MAE (m³/day)	RMSE (m³/day)	MAPE (%)	R^2	Mean Deviation (m³/day)	Stability Rank
Deterministic BRC Design	0.00	0.00	0.00	1.000	0.00	Reference
Multiple Linear Regression	0.24	0.31	7.18	0.884	0.24	5
Random Forest	0.13	0.18	3.91	0.952	0.13	2
Gradient Boosting	0.11	0.15	3.28	0.964	0.11	1
Support Vector Regression	0.16	0.21	4.73	0.936	0.16	3

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Model/Method	MAE (m^3/day)	RMSE (m^3/day)	MAPE (%)	R^2	Mean Deviation (m^3/day)	Stability Rank
Artificial Neural Network*	0.18	0.24	5.26	0.921	0.18	4

6.2 Standards and Reference-Range Comparison

The calculated design parameters were assessed against published fixed-dome and anaerobic-digestion operating guidance to determine whether the selected configuration is technically reasonable [34]. The system operates at a design TS concentration of 8% and HRT of 25 days, producing 110 kg/day of prepared influent from 25 kg/day of human excrement, 19 kg/day of food waste, and 66 kg/day of added water. Maintaining the selected solids concentration is particularly important because Cameroon field investigations have demonstrated that restricted dilution-water availability can cause fixed-dome digesters to operate at considerably higher solids concentrations than intended, adversely affecting biological and hydraulic performance [35]. The 1.232 m^3 governing gas-storage volume, obtained from the conservative TS-based method, exceeds the 0.653 m^3 estimate obtained from the geometric method and therefore provides the controlling storage requirement. Gas treatment incorporates an iron-hydroxide H_2S filter to protect the generator and downstream components from corrosive contaminants [36]. Generator efficiency, methane concentration, gas-pipe integrity, and environmental protection requirements should nevertheless be confirmed during commissioning rather than assumed from theoretical design calculations [37].

Table 3. Designed Parameters versus Reference/Standard Operating Conditions

Parameter	Proposed Design	Reference/Design Requirement	Mean Deviation	Compliance	Engineering Interpretation
HRT	25 days	Mesophilic fixed-dome design basis [34]	To be experimentally determined	Design-compatible	Provides required substrate retention
Total solids	8%	Wet anaerobic-digestion condition [35]	To be experimentally determined	Design-compatible	Supports slurry mobility and digestion
Daily influent	110 kg/day	Feedstock-dependent	—	Design-derived	Obtained from 8.8 kg TS/day at 8% TS
Working volume	2.75 m^3	80% of total volume [34]	—	Design-compatible	Provides active digestion capacity
Total digester volume	3.44 m^3	BRC sizing methodology [34]	—	Design-derived	Matches calculated hydraulic requirement
Digester diameter	1.97 m	BRC geometric relationship [34]	—	Design-derived	Practically constructible geometry
Gas-storage volume	1.232 m^3	Larger of Methods A and B	—	Conservative design	TS-based method governs storage
Biogas production	3.52 m^3/day	Feedstock/yield dependent [36]	Requires field validation	Projected	Combination of both substrates
Electricity generation	5.98 kWh/day	Generator-dependent [37]	Requires field validation	Projected	Based on 1.7 kWh/m^3 conversion
H_2S management	Iron-hydroxide filter	Gas treatment required [38]	—	Incorporated	Protects engine against corrosion
Gas-pipe safety	PVC/HDPE system	Leak-tight compatible piping [38]	—	To be verified	Requires pressure/leak testing

6.3 Robustness and Sensitivity Analysis

The robustness of the design depends principally on whether Hotel X can consistently provide the feedstock assumed during sizing. The baseline calculation requires 25 kg/day of human excrement and 19 kg/day of food waste, giving 8.8 kg TS/day and an estimated 3.52 m^3/day biogas yield. Food-waste availability should therefore be perturbed by ±10%, ±20%, and ±30% to represent fluctuations in meals served, occupancy, and waste recovery

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[35]. Similar sensitivity tests should vary occupancy, TS concentration, HRT, temperature, methane yield, generator efficiency, dilution-water availability, diesel price, and capital expenditure [36]. Feedstock quantity and specific gas yield directly affect biogas production, whereas methane content and generator efficiency principally determine electricity recovery. Diesel price influences financial savings without changing biological performance. Water availability is particularly important because the baseline system requires approximately 66 kg/day of dilution water to maintain 8% TS. Capital cost affects payback and overall economic viability but does not alter the theoretical gas yield [38].

6.4 Integrated Technical-Economic Benchmark Assessment

The integrated results demonstrate an important distinction between technical feasibility and economic attractiveness. Technically, the calculated 3.44 m³ digester can process approximately 110 kg/day of influent and is projected to generate 3.52 m³/day of biogas, equivalent to 5.98 kWh/day or 179.4 kWh/month of electricity. This energy could replace approximately 51.3 litres of diesel monthly. At 800 FCFA/L, the resulting saving is approximately 41,040 FCFA/month, representing a 9.1% reduction in Hotel X's reported monthly diesel expenditure of 450,000 FCFA. These results demonstrate a measurable recurring energy benefit but not, by themselves, strong investment profitability [38]. Capital construction, gas cleaning, generator integration, maintenance, and system operation must also be considered. Regional evidence similarly indicates that biogas-system performance depends on feedstock availability, water, climate, loading, construction quality, cost, and user requirements [39]. The design is therefore technically feasible but economically constrained at standalone hotel scale, while larger hotels and multi-facility systems may benefit from economies of scale and greater aggregate waste availability.

7. DISCUSSION AND CONCLUSION

7.1 Integrated Engineering Interpretation

The study establishes an integrated engineering pathway connecting facility waste generation, feedstock characterization, influent preparation, digester sizing, engineered operating variables, performance prediction, biogas production, electricity generation, diesel displacement, and techno-economic feasibility. For the case-study facility, the combined human excrement and food waste provided 8.8 kg TS/day, requiring 66 kg/day of dilution water to achieve the selected 8% TS concentration. Application of the BRC methodology produced a 3.44 m³ fixed-dome digester with a 1.97 m diameter and 25-day HRT [35]. The calculated biogas production of 3.52 m³/day provides approximately 5.98 kWh/day, demonstrating that hospitality waste represents a quantifiable decentralized energy resource [36]. This output displaces approximately 51.3 L of diesel monthly, corresponding to 41,040 FCFA/month in fuel savings. Nevertheless, the resulting 9.1% diesel-cost offset shows that the system supplements rather than replaces the hotel's conventional backup generation. Its significance therefore extends beyond electricity alone to waste recovery, reduced diesel dependence, and potential environmental benefits [37].

7.2 Practical Deployment, Policy, and Limitations

Practical deployment is influenced by seasonal occupancy, variations in food-waste generation, water availability, effective feedstock segregation, digester maintenance, gas cleaning, skilled operation, generator efficiency, land requirements, and safety management [38]. Food-waste grinders or macerators should be incorporated during pretreatment to improve substrate homogeneity and facilitate digestion. The calculated outputs also remain design-based projections requiring confirmation through long-term operating measurements. Capital affordability represents a particularly important limitation because the modest energy-cost offset may be insufficient to recover construction and equipment costs rapidly [39]. Consequently, centralized plants serving clusters of hotels and residential facilities should be considered where individual facilities lack sufficient feedstock or economies of scale. Government subsidies, concessional financing, equipment tax incentives, and carbon-credit mechanisms could reduce investment barriers [40]. Economic assessments should additionally incorporate avoided waste-management costs rather than considering diesel savings alone. These measures could improve the commercial viability of biogas while simultaneously addressing waste-management and decentralized-energy objectives.

7.3 Conclusion and Future Research

This study developed an integrated engineering, data-driven, and techno-economic methodology for converting organic waste generated by hotels and residential facilities in Cameroon into useful electricity. Using a case-study facility in Buea, the BRC fixed-dome methodology produced a 3.44 m³ digester with a diameter of 1.97 m, designed for co-digestion of human excrement and food waste. The system is projected to generate 3.52 m³ of biogas per day and 5.98 kWh of electricity daily, demonstrating the technical potential of hospitality-sector organic waste as a decentralized energy resource. The resulting 9.1% diesel-cost offset represents a meaningful but modest contribution to facility energy requirements and indicates that technical feasibility does not automatically establish economic attractiveness.

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The scalability assessment further indicates that digester capacity, feedstock requirement, biogas production, and electricity generation can be adapted to facilities of different sizes. However, proportional increases in both energy supply and facility demand mean that increasing facility size alone may not substantially improve the percentage energy offset. Greater economic benefits may therefore arise from centralized multi-hotel and residential systems, where aggregated waste streams, shared infrastructure, and distributed capital costs can create stronger economies of scale.

Future research should prioritize full-scale prototype construction and long-duration monitoring to validate the calculated gas and electricity outputs under actual operating conditions. Methane sensors and IoT-based monitoring should be incorporated to continuously measure temperature, gas composition, pressure, feed rate, and production performance. Larger multi-hotel datasets could support real-time performance prediction, dynamic process-control simulation, and advanced machine-learning optimization. A complete lifecycle cost-benefit assessment should incorporate construction costs, maintenance, generator replacement, avoided waste-disposal expenditure, digestate value, and potential carbon-credit revenue. Further work should examine policy mechanisms successfully applied in other African countries and assess their applicability to Cameroon. Life-cycle environmental assessment, digestate valorization, centralized facility networks, and hybrid biogas-solar-storage systems should also be investigated as pathways toward more economically and environmentally sustainable decentralized energy systems.

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